Galaxy cluster detection on optical images using Deep Machine Learning

Kirill Grishin (APC, IN2P3, France)
Simona Mei (APC, IN2P3, France)
Stephane Ilic (PSL)

submitted to A&A, astro-ph: 2301.09657

DESC project : Project: [226] Cluster Detection with Deep Learning Networks

- We use Deep Learning Networks to detect optical galaxy clusters and explore different network architectures to derive cluster position and parameters in DC2 and publicly available DES Y1 data. In particular, we will start with the Yolo software, which has been previously applied to SDSS data, then extend to Bayesian Neural Networks. We will compare results with basic CNN and conventional cluster finding methods using the DESC tool, CLEVAR, and will characterize the selection function of our cluster finding algorithms.
- Jim Annis, Camille Avestruz, Dominique Boutigny, Mariano Dominguez, Kirill Grishin, Simona Mei (lead), John Stott + Michel Aguena, Céline Combet, Marie Paturel, Florian Ruppin, ++15 people on Slack channel

#desc-cl-clfinder-yolo

How we can identify galaxy clusters

Galaxy cluster are the **largest gravitationally bound structures** in the Universe. They are the best places to test cosmological models.

Spectroscopic surveys:
Advantages:

- No systematics in redshift estimate
- Dynamical mass measurement assuming that clusters are the virialized systems.

Disadvantages:

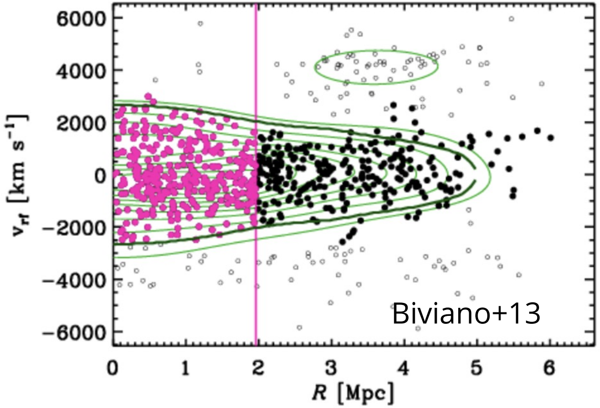
- Limited sample
- Need bright sources or larger exposure time
- For high-z objects need prominent features in spectra like emission lines

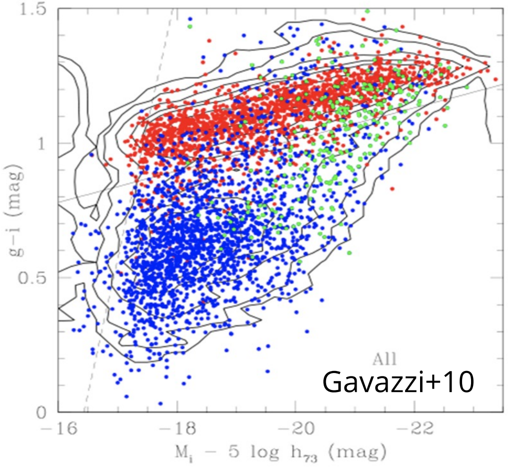
Imaging surveys:
Advantages:

- Cover wide areas on the sky
- Do not need high exposure times like for spectroscopy

Disadvantages:

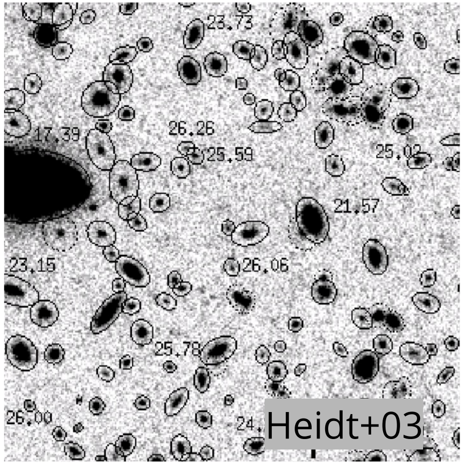
- The mass proxy (e.g., richness) has large scatter
- Photometric redshift measurements might be affected by systematics

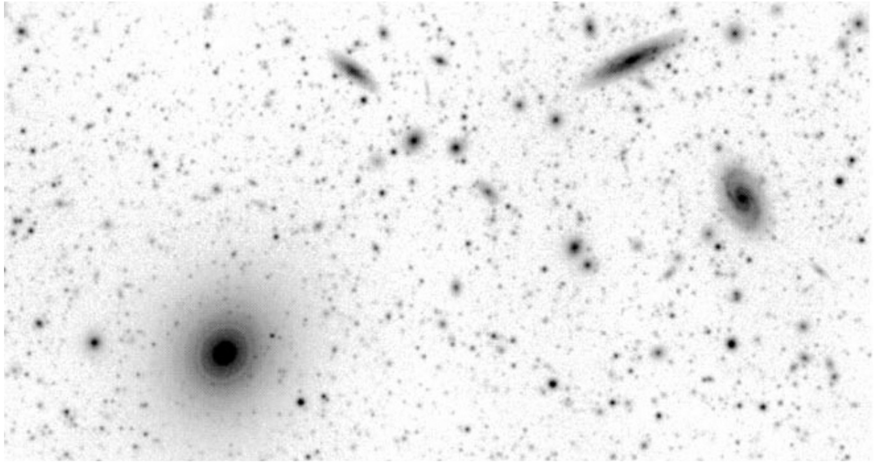




Galaxy cluster detection on composite color images: Motivation

- ➢ We use all the information contained in images
- ➢ We do not need to make photometric and photometric redshift catalogs – we eliminate one (middle) step that can lead to bias
- ➢ ML algorithms can be much faster than usual methods



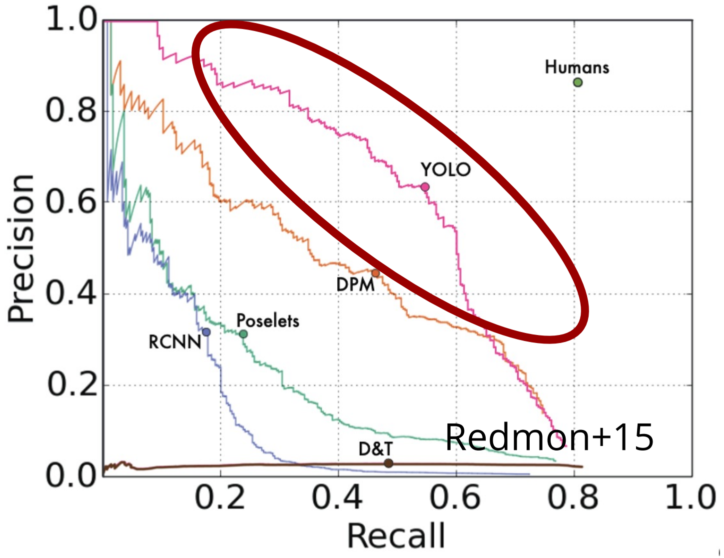


ML for object detection and for cluster detection

Deep Machine Learning techniques are widely used in Astrophysics for the analysis of the data from large area surveys (e.g. Huertas-Company & Lanusse 2022)

Chan & Stott (2019) demonstrated that convolutional neural networks can be used for galaxy cluster detection with high purity (75%) and completeness (80%) when trained on Wen+12 sample and validated on redMaPPer catalog of galaxy clusters (Rykoff+13).

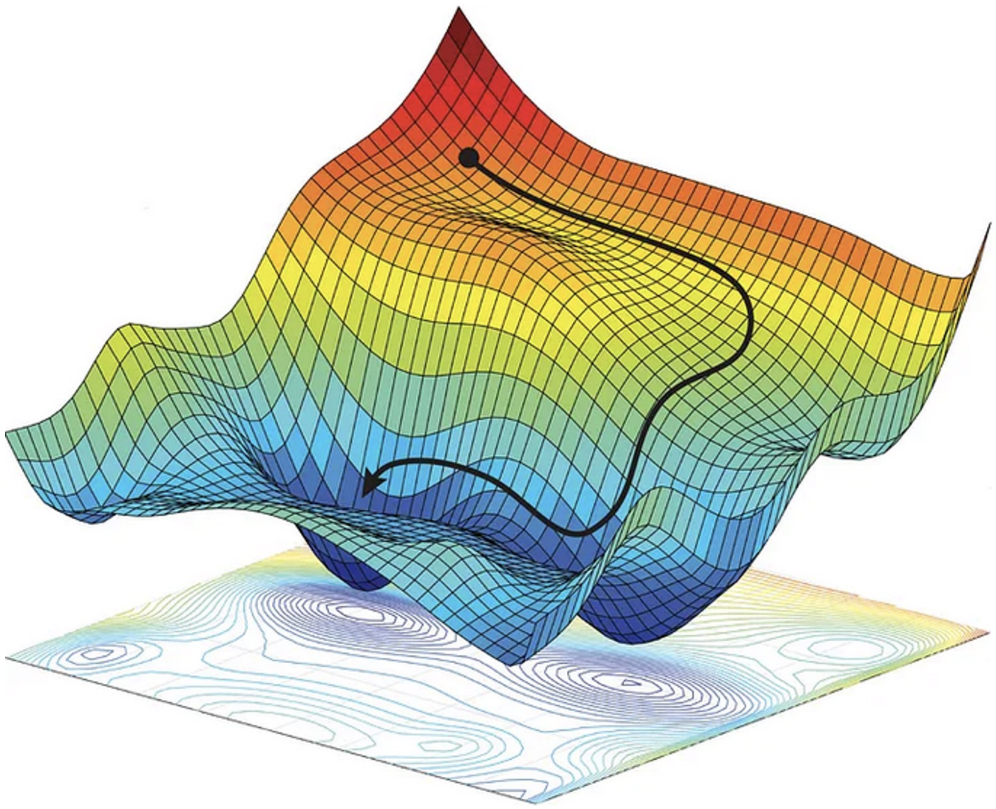
The YOLO convolutional network is widely used for object detection in general and for object detection and classification in astrophysics (Gonzalez+18, He+21). It performs much better than other networks.



Network learning process

Our goal is to find the values for the parameters where the function of errors (“loss function”) reaches its minimum.

But we have a larger number of parameters → our problem cannot be solved by the conventional methods of the functional minimization, e.g. Levenberg-Marquardt.



Network learning process

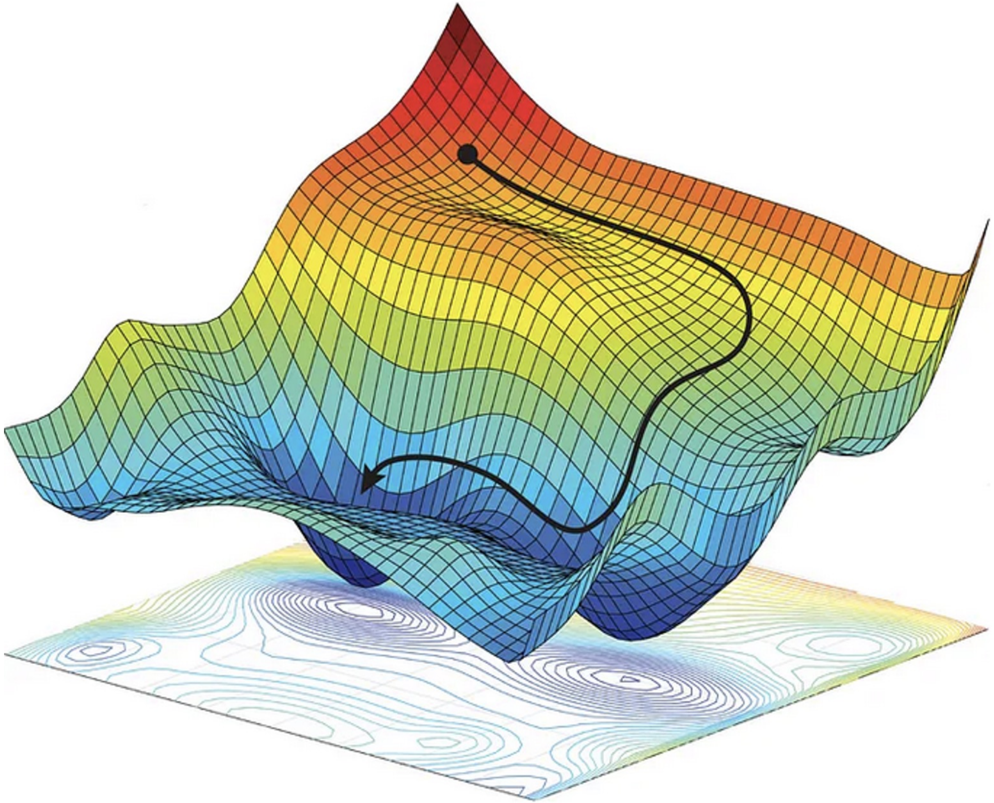
In the training procedure we use similar approach as in non-linear minimization:

Iteration → Epoch

Step size→ Learning rate

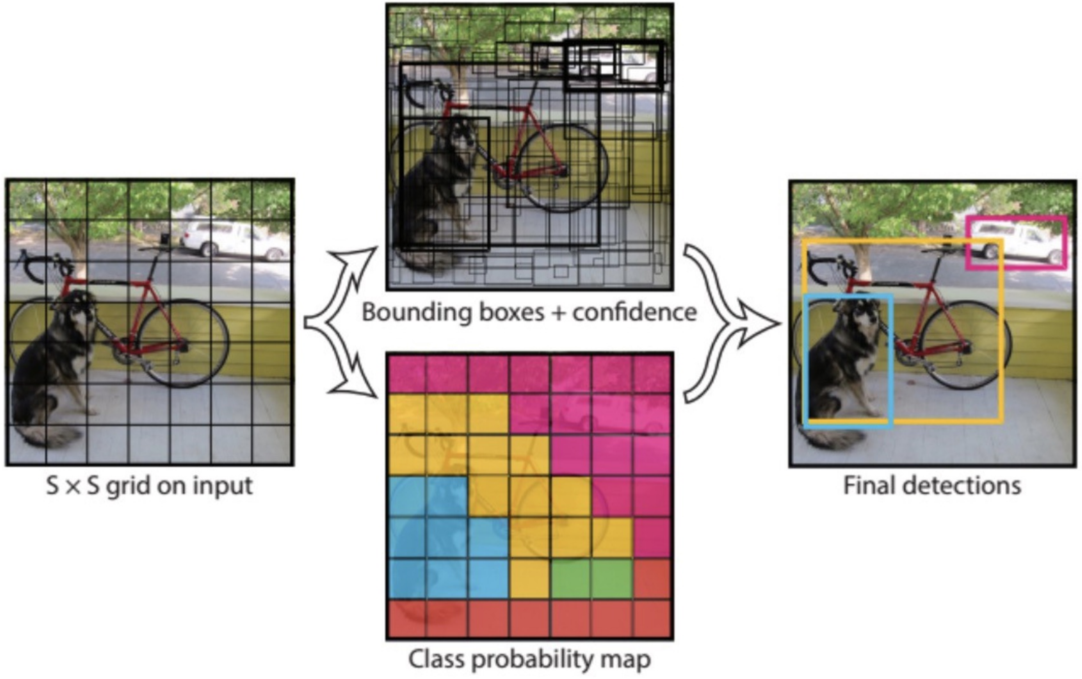
Model parameters → Weights

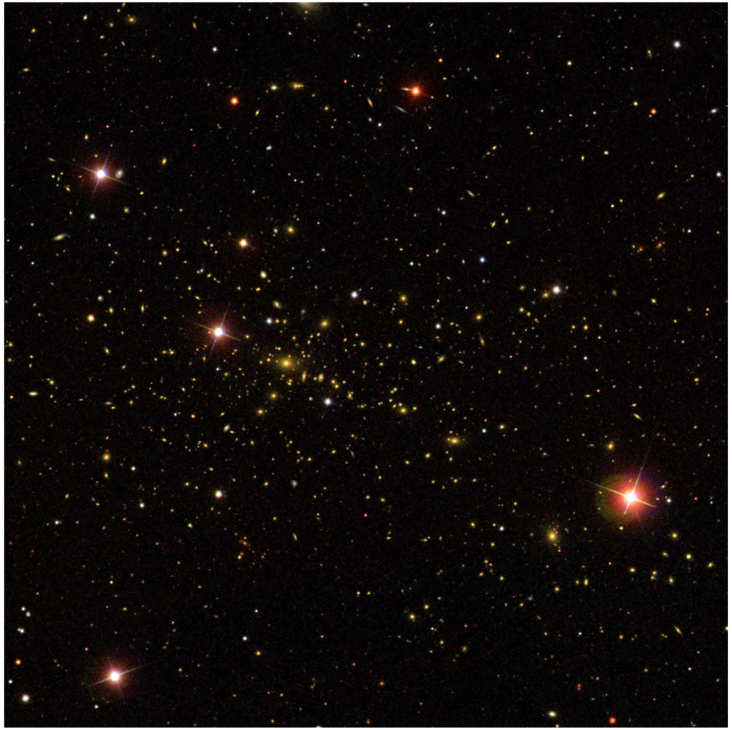
But given higher dimensionality we need to validate the training process with a different sample



YOLO (Redmon et al. 2016, 2018)

- The YOLO network is based on a Deep Convolutional network (Darknet53) and it is used for fast object detection in images (e.g., animals, cars, people, etc.)





YOLO-CL: YOLO for CLuster detection

We introduced the following changes to Yolo v3:

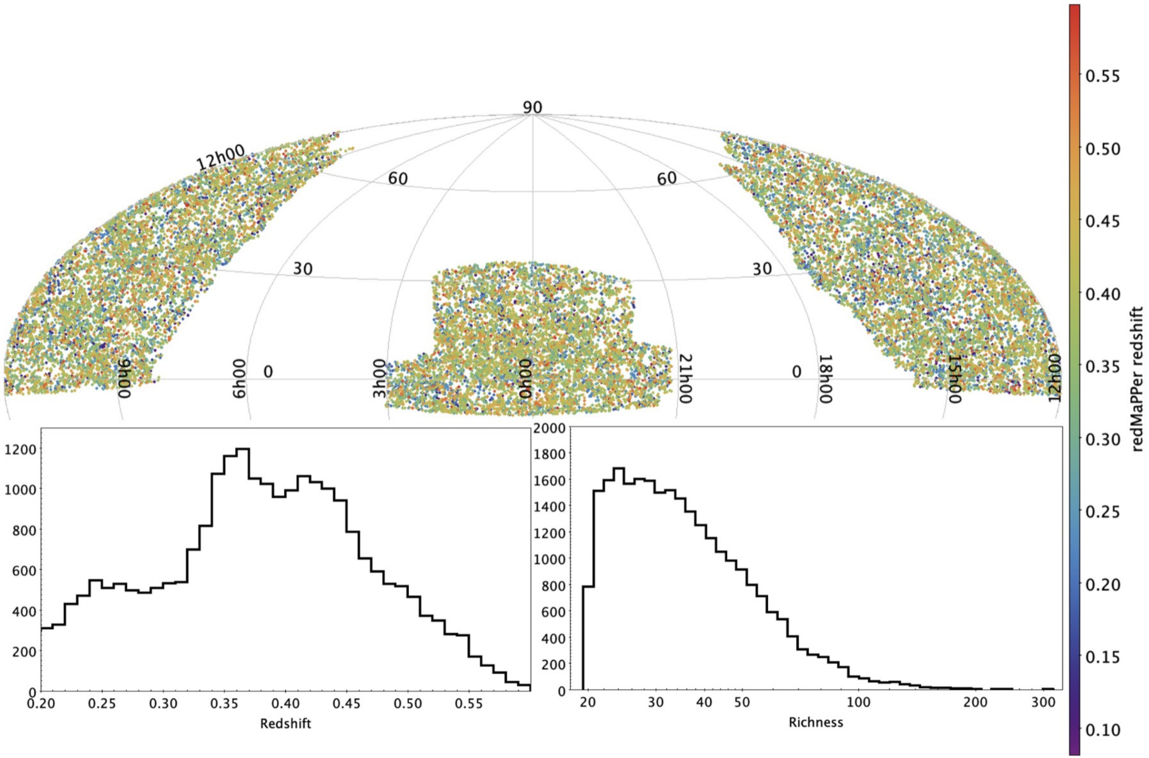
- We left only one object class – “cluster”
- We used gIoU (Generalized Intersection over Union) criteria to eliminate multiple detections:

$$\mathrm{gIoU} = \mathrm{IoU} + \frac{\mathcal{U}}{\mathcal{A}_c} - 1$$

We called the final version of the Yolo v3 CNN network with all the modifications above as YOLO-CL: YOLO for CLuster detection.

Grishin, Mei, Ilic, astro-ph: 2301.09657

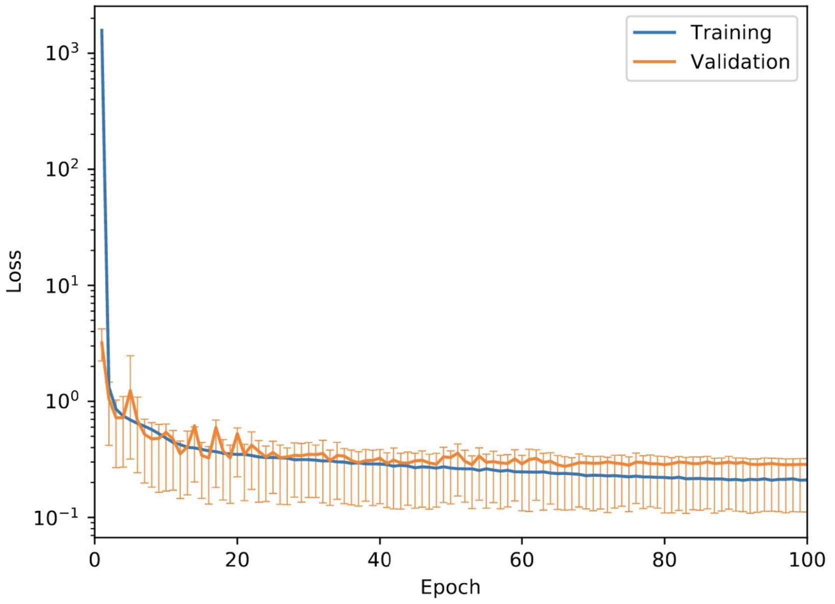
redMaPPer sample used for the training and the validation of YOLO-CL



Grishin, Mei, Ilic, astro-ph: 2301.09657

YOLO-CL training on SDSS images for redMaPPer clusters

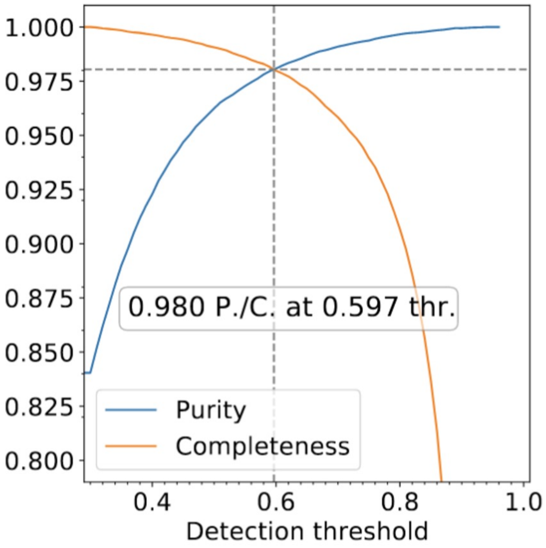
- ➢ Our YOLO-CL network was trained on SDSS images for redMaPPer clusters
- ➢ The training dataset contained ~12000 galaxy clusters + 12000 random field images
- ➢ Validation dataset contained ~12000 galaxy cluster + 12000 random field images
- ➢ We run training for 512x512 and 1024x1024 images

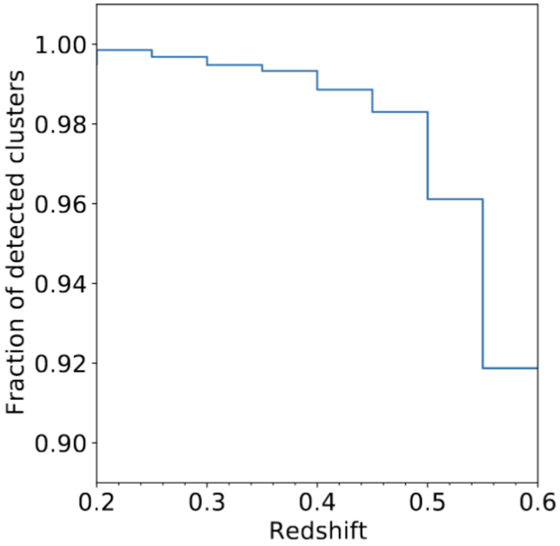


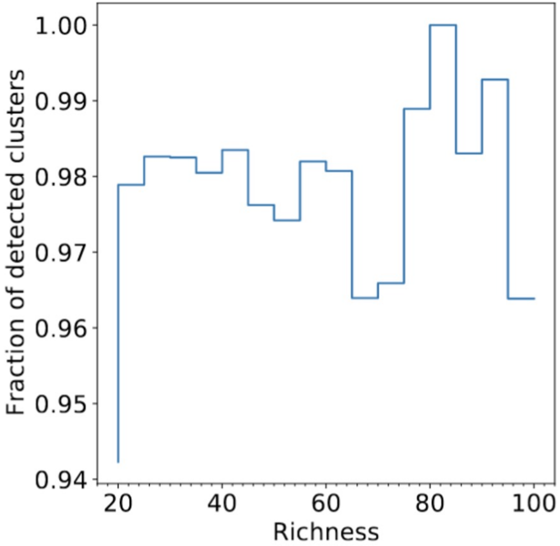
Grishin, Mei, Ilic, astro-ph: 2301.09657

YOLO-CL performance on redMaPPer clusters

We were able to reach 98% of purity and completeness at a probability threshold of 0.6. We mainly miss high redshift clusters, badly covered by the SDSS depth.



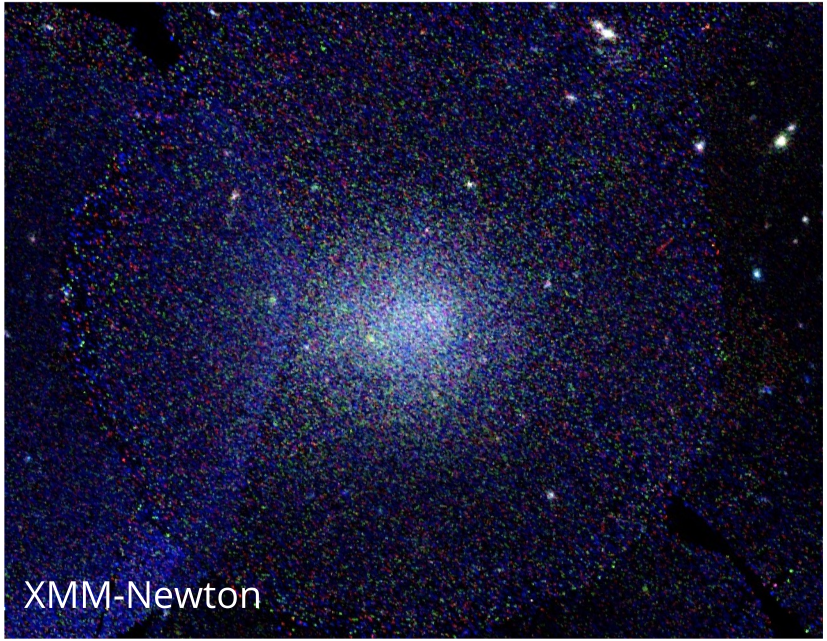




Grishin, Mei, Ilic, astro-ph: 2301.09657

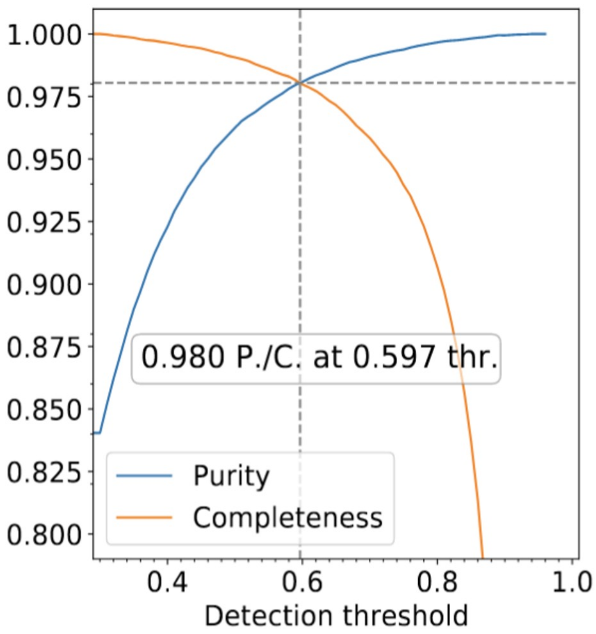
A sample of independently selected clusters

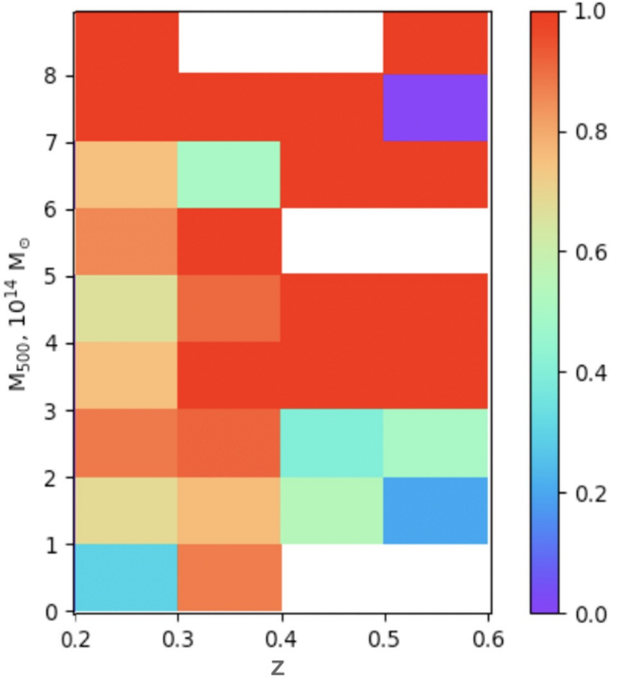
Galaxy clusters are the main sources of the X-Ray diffuse emission in the Universe.

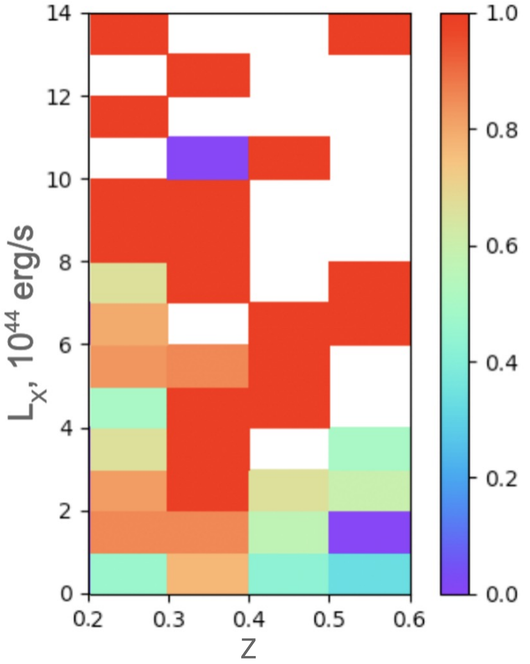


YOLO-CL performance on MCXC clusters

We reach 100% of completeness for clusters at z>0.4 and $M_{500} > 3\times10^{14}\ M_\odot$







Grishin, Mei, Ilic, astro-ph: 2301.09657

X-ray surface brightness and comparison to redMaPPer

YOLO-CL reaches deeper than the training sample – it learns patterns and features of clusters.

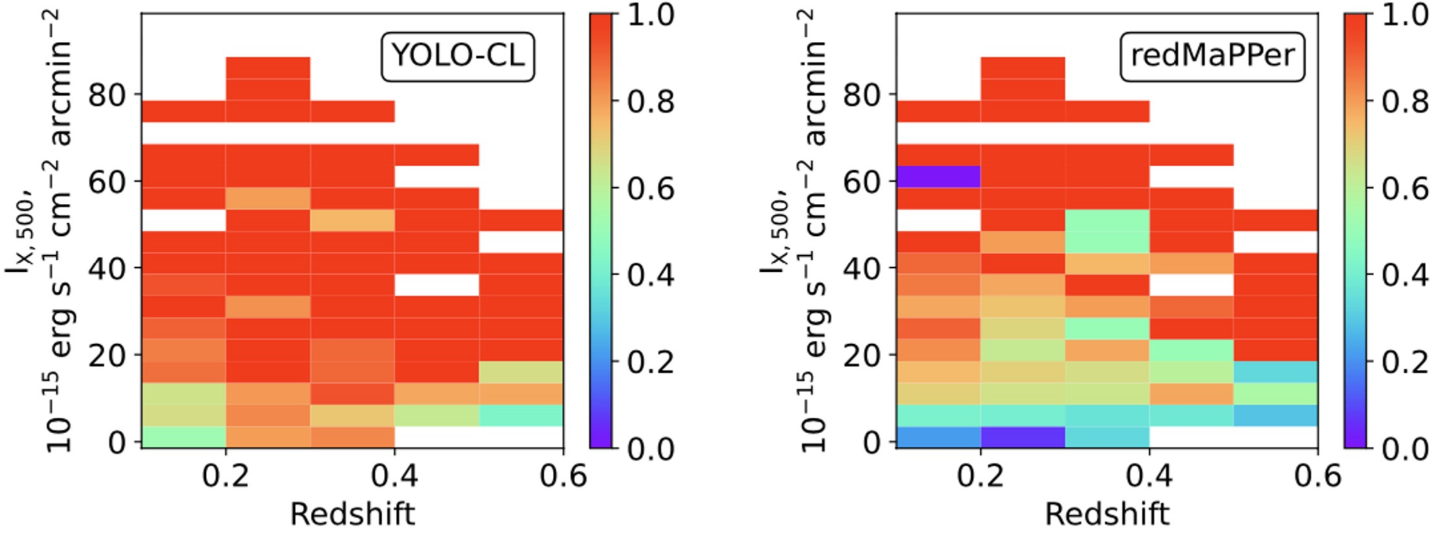


Fig. 10. The YOLO-CL and redMaPPer MCXC2021 cluster detection completeness as a function of redshift and mean X-ray surface brightness. Left: YOLO-CL detects ~ 98% of the MCXC2021 clusters with $I_{X,500} \gtrsim 20 \times 10^{-15}$ erg/s/cm^2/arcmin^2 at $0.2 \lesssim z \lesssim 0.6$ and ~ 100% of the MCXC2021 clusters with $I_{X,500} \gtrsim 30 \times 10^{-15}$ erg/s/cm^2/arcmin^2 and $z \gtrsim 0.3$. Right: redMaPPer detects ~ 98% of the MCXC2021 clusters with $I_{X,500} \gtrsim 55 \times 10^{-15}$ erg/s/cm^2/arcmin^2 at $0.2 \lesssim z \lesssim 0.6$ and ~ 100% of the MCXC2021 clusters with $I_{X,500} \gtrsim 20 \times 10^{-15}$ erg/s/cm^2/arcmin^2 at $0.5 \lesssim z \lesssim 0.6$. On the right of each figure is the completeness scale. From this comparison, YOLO-CL is more complete than redMaPPer in detecting MCXC2021 clusters.

Grishin, Mei, Ilic, astro-ph: 2301.09657

Conclusions

- ➢ With YOLO-CL we were able to reach 98% of purity and completeness for redMaPPer detected clusters in SDSS
- ➢ When using X-Ray surface brightness to assess the performance of different cluster detection algorithms, YOLO-CL reaches deeper than the redMaPPer training sample